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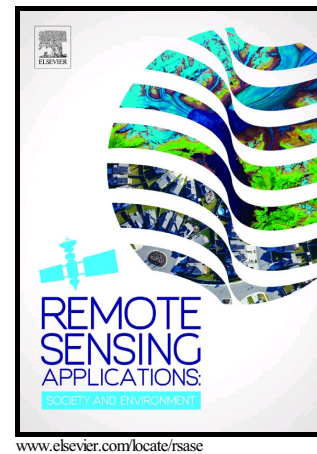
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Discriminating Uranium and Copper Mills Using Satellite Imagery

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Abstract

Identifying uranium mills from high resolution commercial satellite images has assumed significance in recent years because of non-proliferation concerns. Studies have shown that it is difficult to identify Uranium mills through remote sensing methods that use only spectral signatures. In this communication we suggest an approach that relies only on spatial signatures of the equipment used in the extraction process as an alternative. Since the extraction of Uranium and Copper have many similar features especially where Copper is extracted from low grade ore or from copper tailings, there could be ambiguity in identifying a Uranium mill from high resolution commercial satellite images. In an earlier work carried out by the authors and summarized in this paper as well we had proposed a separation between copper and uranium mills based on the spatial signatures of equipment that is unique to the copper milling process. In this paper we suggest some improvements to the methodology outlined by us in our earlier work. In addition to the other features used to separate Uranium and Copper mills we bring in the dimensions of common equipment used in both processes as an additional dimension to improve the robustness of our classification. This technique is applicable only where the extraction is done in a mill and not where Uranium is extracted by in situ leaching methods.

Keywords: Uranium mill, Copper mill, Spatial Signatures, Discriminant function

1. Introduction

Uranium in its varied forms is a very important nuclear material. Since Uranium has military as well as civilian uses, monitoring the uranium production on a global basis is essential. The International Atomic Energy Agency (IAEA) an independent intergovernmental, science and technology-based organization [1], that serves as the global focal point for nuclear cooperation verifies through its inspection system that States comply with their commitments, under the Non-Proliferation Treaty and other non-proliferation agreements, to use nuclear material and facilities only for peaceful purposes.

Following the IAEA suggestion [2] in 1990 that civil remote sensing satellites could be used to monitor multilateral agreements such as the 1970 Treaty on Non-Proliferation of Nuclear Weapons (NPT) a number of studies [3, 4, 5] on the use of commercial satellite imagery in safeguards procedures were carried out under the UK and German Support Programmes to the IAEA. Basically in these studies various elements of the nuclear fuel cycle were investigated in order to determine “keys” for each of the nuclear facilities so that an image interpreter could identify them in a satellite image. A number of recommendations [6] were then made by the Director General’s Standing Advisory Group on Safeguards Implementation (SAGSI) to strengthen the IAEA’s safeguards procedures that included the use, by the Agency, of open source information such as images acquired by commercial satellites. Later the early part of the fuel cycle, uranium mines and mills, were investigated and a preliminary report [7] was prepared for the Research Centre, Jülich, Germany. The Agency is now using this technique to confirm declarations made by States under their safeguards agreements with the Agency, as a pre-inspection planning tool and to look for undeclared nuclear activities[8].

Identifying a Uranium exploration facility or a Uranium mill, was difficult during the early years of remote sensing because of the low spatial and

spectral resolution of satellite sensors. Attempts were made by the CIA, USA to monitor Uranium mining and milling activities in the Former Soviet Republic (FSR) and also estimate the production [9] based on the ore grade and the size of the tailings ponds using aerial photographs. Later low resolution satellite images became available with the launch of the CORONA satellite by the USA. These studies also helped to define what can be learnt about Uranium mining and milling using satellite imagery leading to the publication of the Photo Interpretation Handbook [10].

With the availability of hyper-spectral images and advanced image processing techniques, there has been renewed interest in identifying a Uranium mill using spectral signatures [11, 12, 13, 14]. A systematic study to evaluate the use of satellite remote sensing for identifying Uranium mines and mills was carried out by Researchers at the Sandia National Research Laboratory [15]. Using the Ranger Uranium mill in Australia as a case study, the report looked at the potential use of multi-spectral as well as hyper spectral data from a number of remote sensing satellites to determine whether there were any unique features of a typical Uranium mining and milling operation. The study concluded that although hyperspectral data could help in categorizing different bodies of ore into very broad types, the occurrence of Uranium within such an ore body is so small that it provides no visible signature to the satellite sensor. The study also concluded that hyper-spectral data could not distinguish between uranium milling processes from other milling processes such as that of copper, zinc, vanadium, phosphorous and Rare Earths. Further the study pointed out that while high spatial resolution satellite systems such as Quickbird lack sufficient spectral resolution to uniquely identify many materials, spatial information provided by these systems could complement information obtained from high spectral resolution systems such as Hyperion.

Taking the cue from the above study, a set of functional keys and signatures based upon observations of a large number of Uranium milling operations across the world for which Google Earth (GE) imagery and

associated process flow diagrams were readily available was developed more recently by Chandrashekar et al. [16]. Satellite imagery especially Google Earth (GE) images were then studied to generate a set of interpretation keys. These keys link the operations in the mill sites to the observables in the satellite image. The shapes and sizes of the features seen and their position in the process chain provided a set of spatial signatures that could be used to identify a Uranium mill. The most commonly occurring features across the sample set along with their signatures were then used as the basis for the development of a decision tree. The method also provided a way in which one could make an estimate of the production capacity of Uranium mills [17, 18].

The investigation showed that the extraction process of copper was very similar to that of uranium extraction process particularly where copper was being extracted from its tailings or when the ore grade was low. Some of the equipment used in both these extraction processes was similar. It was therefore important to make sure that a copper mill was not wrongly labeled as a uranium mill and vice-versa. Towards this the study identified spatial features such as an electro-winning building associated with Copper mills that is not present in a Uranium mill. This helped to identify a uranium mill with more confidence.

In this paper we present an extension of the above study to identify a Uranium mill and discriminate it from a Copper mill. This discrimination is made possible by taking into account the sizes of common equipment used in the extraction processes of both Uranium and Copper. We show that the differential sizes of Counter Current Decantation (CCD) units seen in both Uranium and Copper mills can be used to discriminate the two extraction facilities. This together with the spatial signatures of electro-winning building and power plants invariably present in a copper mill make the decision algorithm for identifying a uranium mill and discriminating it from a copper mill, a robust one.

The spatial signatures and the approach suggested could be suitably modified for use as primitives for object based image analysis [19, 20]. This paper does not deal with heap leaching or with in situ leaching [ISL] operations which may involve different observables in the satellite imagery. It only covers general hydrometallurgical milling operations involved in Uranium extraction. Since ISL mills also have some recognizable surface features [7], an extensive investigation ISL mines and mills across the world will help to identify spatial signatures for such sites.

2. The Uranium Extraction Process

The geological conditions under which Uranium bearing ores can be found across the world have been extensively researched and documented [21]. The various steps involved in mining, beneficiation of the ore and its further processing into the commonly used yellowcake form has also been studied in great detail. Uranium Mining is carried out either through underground or open pit mines.

The nature of the deposit dictates the choice of the process adopted at a particular site.

An overview of the typical processes used for the extraction of Uranium is in Figure 1. The figure also shows typical equipment used to achieve the required result at each step. There may be other equipment used in the process. These are however, not mentioned here, since the focus is on using the satellite image for the identification of the equipment used for the key processes rather than on the overall facility itself. Our objective is to determine which of the equipment used in a Uranium milling operation, are visible and identifiable in a satellite image.

After the ore is crushed and ground suitably, Uranium is leached into a solution form through the use of acids or alkalis. The mineral composition of the ore determines what kind of leaching process is carried out in a mill.

Leaching can be performed in specialized tanks, in heaps, or in situ. High grade Uranium ores are generally leached in tanks, while lower grade ores are leached in heaps or in situ.

For the purpose of this study we have not considered those mills that use heap leaching as the only method for leaching. The reason for this omission is that the process steps involved in this case will differ slightly and it may not be possible to uniquely identify such mills in a satellite image.

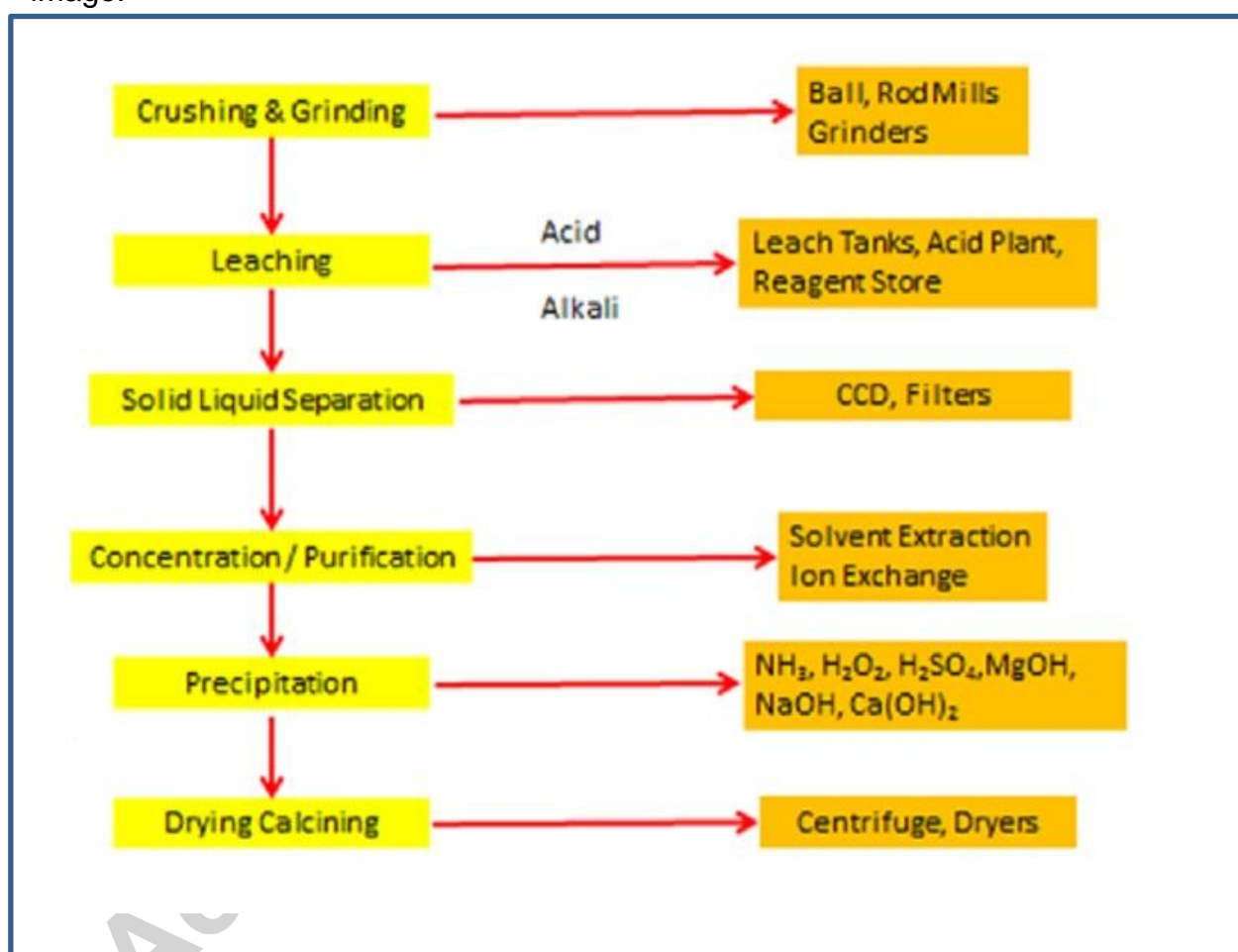


Figure 1 Steps in Uranium Extraction

A solid-liquid separation step follows the leaching step. This is done using Counter Current Decantation (CCD) thickeners and filters. In principle if the leached liquor contains a sufficient concentration of Uranium it can be directly precipitated. This is rarely done and the leached solution is subjected to either solvent extraction or ion exchange process.

The last step is the recovery of solid Uranium or yellow cake from the solution. This involves precipitation and drying.

3. Copper Extraction Process

An overview of a typical Copper extraction operation is available in the Sandia report [9].

Copper occurs mostly in the Sulphide or Oxide forms. While the crushing and grinding steps are common to all extraction processes, the process steps that follow may be different for the two types of ore.

The major steps involved in a Copper extraction process are shown schematically in Figure 2.

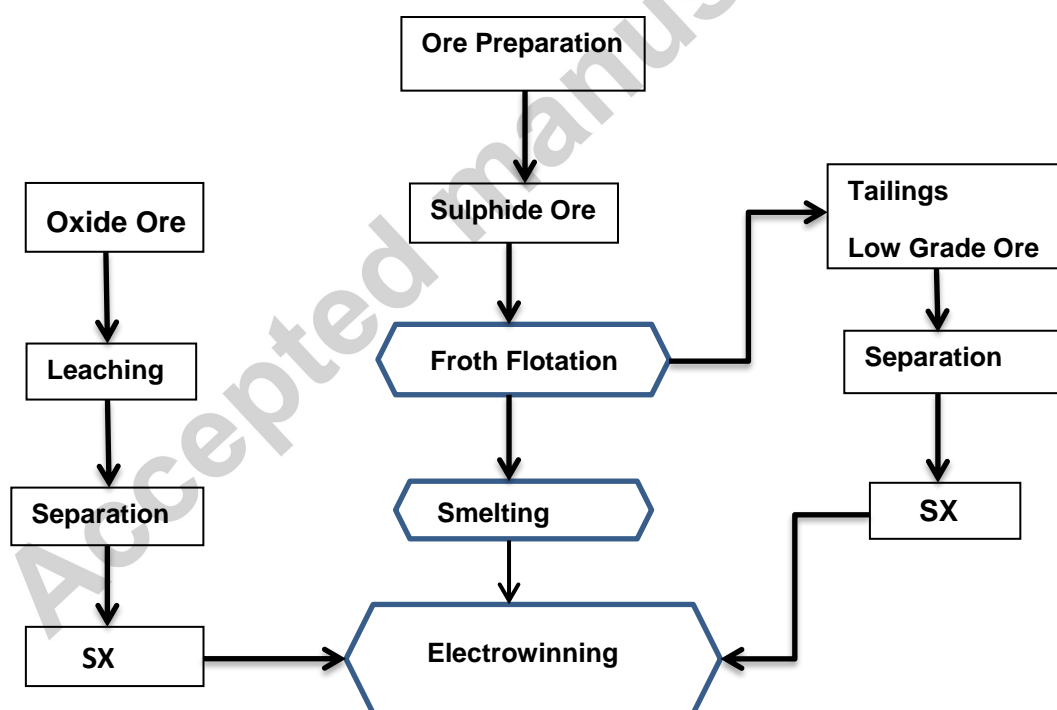


Figure 2 Steps in Copper Extraction

The Sulphide ore goes through a froth flotation process after the initial crushing and grinding which concentrates the Copper part. The froth from the flotation process contains the bulk of the Copper. The froth is dried and then sent directly to a smelter. The smelter may be located at the mill site or may be located elsewhere. The smelter converts the Copper concentrate into blister Copper which is further refined to produce anodic Copper. Anodic Copper finally goes through an Electro-winning step to produce high purity Copper.

The tailings from the froth flotation may also contain Copper which could be recovered. These tailings are leached with sulphuric acid, passed through a series of CCDs followed by a solvent extraction step. The Copper solution that comes out of the solvent extraction step is then sent to an Electro-winning facility for the extraction of Copper.

Copper occurring in the oxide form is typically leached using sulphuric acid after suitable crushing and grinding. Following concentration through a solvent extraction process the solution containing Copper is sent to an electro-winning facility. Depending on the concentration of the ore the leaching step may also be followed by a CCD sequence prior to solvent extraction and electro-winning.

4. Key Characteristics of a Uranium Mill

By interpreting the Google Earth (GE) images of a large number of commercial Uranium mills across the world we build a set of keys for identification of a Uranium mill based on the spatial features of the equipment used in the milling operations instead of looking for spectral signatures. A comprehensive understanding of the spatial signatures of the Uranium operations at each site is built up using the process flow sheets of the mill along with publicly available information about the mill.

Together with the GE image of the mill, the keys for identification are developed. The most commonly occurring features in the sample sets along with their signatures are then used to decide whether a mill seen on a satellite image is a Uranium mill or not.

Our objective is to determine which of the equipment are unique to a Uranium milling operation and visible and identifiable in a satellite image.

Towards this we selected 11 Uranium milling operations and our sample set is shown in Table 1.

The imagery available on GE for each of these mills was studied in detail along with other publicly available information.

The set of observables that we could identify from these images formed the basis for identifying the key observables needed to identify a Uranium mill. For a complete analysis of the GE images of these mills see Chandrashekar et al. [16].

Table 1 Sample set of Uranium Mills analysed

Country	Mill Name	Location (Lat / Long)
USA	Sweet Water	42 03 N 107 54 W
Canada	Rabbit Lake	58 15 N 103 40 W
Australia	Ranger	12 41 S 132 55 E
Canada	McLean Lake	58 21 N 103 50 W
Canada	Key Lake	57 13 N 105 40 W
Niger	Arlit	18 47 N 7 21 E
Namibia	Rossing	22 28 S 15 03 E
Namibia	Langer	22 49 S 15 20 E
Russia	Krasnokamensk	50 06 N 118 11 E
Czech Republic	Rozna	49 30 N 16 14 E
Romania	Feldiora	45 50 N 25 30E

Figure 3 is a Google Earth image of a Uranium mill and shows how the crushing/ grinding, leaching section, CCDs, and Solvent Extraction buildings appear in such an image.

Though crushing, grinding and slurry preparation facilities are identifiable in most of the images they do not offer any special features associated with only a Uranium Milling operation.

The most commonly visible feature in the satellite image is the Counter Current Decantation (CCD) unit, used in the solid / liquid separation process.

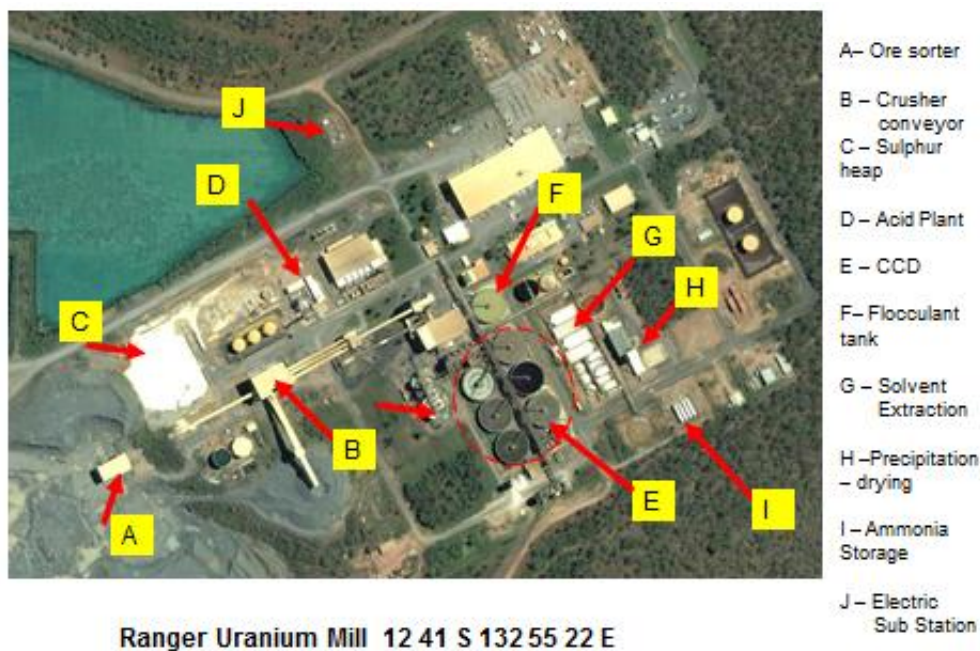


Figure 3 Google Earth Image of a typical uranium Mill

There are several features associated with the leaching process. Some feature or the other is seen in all the mills. In the case of acid leaching one can see either the acid plants or the leach tanks and sometimes the acid storage tanks close to the leaching facility. Since alkaline leaching involves higher temperatures; one can look for evidence of chimney, heat exchangers or even smoke. Although the leaching facility is difficult to identify and may require more detailed knowledge of the processes being employed in the mill, there are other ways in which we can locate this activity within the mill. Since we know that the leaching operation follows the ore preparation step and precedes the solid liquid separation step the sequence of operations helps one to identify some of the leaching features.

The next feature of interest is the equipment associated with the process of concentration and purification. In most mills this is done using either the solvent extraction (SX) columns or the ion exchange (IX) process. Occasionally a combination of both may be used. The SX columns are housed inside a building and may not be readily identifiable. In our sample mill sites we however noted that the SX columns are housed inside a sequence of identical buildings and linked to these are the storage tanks containing the solvents used in the SX process.

The IX columns are usually left in the open and are visible in the satellite image.

The features associated with precipitation, drying and calcining are not uniquely identifiable in a satellite image. In most cases they have to be identified indirectly by the presence of containers holding solvents and reagents used for this purpose. Proximity to the SX or IX facilities of such features is another aspect that we can use to identify this facility. In some of the mills where ammonia is used, the ammonia cylinders are seen clearly in the satellite image.

Essentially our procedure for identifying a Uranium mill from a GE image is to first identify the CCD circuit; then try to locate the leaching facility upstream. If the CCD process is followed by a SX or IX facility, we could conclude with high level of confidence that the facility is a Uranium mill.

This approach has certain limitations because many other mineral extraction processes are very similar to the Uranium extraction process. Of these, it is most difficult to discriminate Copper and Uranium extraction processes in a satellite image. By identifying spatial features that are unique to Copper mills, we will be able to better differentiate and separate a Uranium mill from a Copper mill.

5. Differentiating features of a Uranium Mill from a Copper Mill

There are many process steps that are common to both Uranium and Copper. However Copper and Uranium differ in some of the process

details. These can be used to separate out a Copper mill from a Uranium mill.

One major difference between a dedicated Uranium Mill and a dedicated Copper mill has to do with the scale of operation. For economic viability Copper mills have to produce much larger outputs than Uranium mills. Thus invariably a Copper mill is at least 2 to 3 times larger than a Uranium mill.

A mill which processes low grade Copper ore or a part of a Copper mill which processes the tailings from a froth flotation process will look similar to a Uranium mill. It will have the features such as CCD circuits, SX units in addition to the acid leach facilities that we have seen in a Uranium mill. However, the differentiating factor for the extraction of Copper from flotation tailings is that after solvent extraction it goes to an electro winning facility instead of a precipitation facility. Since such an electro winning facility has a typical signature evidence of this step in a satellite image can be used to separate out a Uranium mill from a Copper mill.

Figure 4 is the Google Earth image of a Copper tailings mill at Nchanga Copper mill at Zambia. We can see features in the image which are similar to the features seen in a Uranium mill.

For example, the CCDs are seen in this extraction plant. There are also a series of solvent extraction steps each housed in a separate but similar building. We also see a Power Plant. In addition, we see the Electro-winning building which is not seen in a Uranium mill. The differentiating factor for the extraction of Copper from flotation tailings is therefore this facility. After the solvent extraction process, instead of a precipitation facility which is seen in a Uranium mill, in the Nchanga Copper mill we see an electro-winning facility. Since such an electro-winning facility has a typical signature, evidence of this step in a satellite image can be used to separate out a Uranium mill from a Copper mill.

The Electro- winning facility has a typical structure shown in Figure 5. In the figure the long building is an electro winning facility which can be

easily identified. Usually this is located close to the solvent extraction facility.

Another differentiating feature has to do with the dimensions of the CCDs. The economies of scale for Copper production are significantly greater than the scale economies needed for Uranium production. This will require higher ore grade materials as well the processing of a larger volume of materials in a Copper mill. The size of the equipment and the overall size of the plant are also likely to be much bigger. If CCDs are used in the production process it is quite likely that the diameter of these CCDs will be much larger for Copper than for Uranium. A detailed investigation of the CCD diameters of various Copper mills was undertaken to verify whether this is true. This is discussed in greater detail in the following section.



Figure 4 Nchanga Copper Tailings Mill (12 31 58S 27 50 47E)

A – Acid Plant, B – Leaching, C – CCD, D – Solvent Extraction, E – Electro winning, F – Power Plant



Figure 5 A typical Electro-winning Building seen in a GE image

6. Dimensions of the CCD Equipment

We have seen that the CCDs are common features in Uranium and Copper mills. Though not always present in Copper extraction plants, they are invariably present when the Copper tailings are being processed. In such cases we need to find a method to ensure that we do not wrongly classify a Copper mill as a Uranium mill. Occasionally, it is possible that in a mill we see a series of CCDs, but no other distinguishing feature to clearly mark it as a Uranium mill. This can happen if we do not see an Electro-winning facility in the vicinity, although there may be buildings which look like solvent extraction buildings.

In this case how do we take a decision? During our investigations into the Uranium Copper mill separation problem, we noted that the CCD dimensions of Copper mills are larger than the CCD dimensions of Uranium mills. We therefore compared the CCD diameters from a sample of Copper mills with the CCD diameters from Uranium mills.

Our sample data consist of 10 Copper mills and 14 Uranium mills. The sample data are shown in Table 2. The Copper mills are located in Mexico, USA, Indonesia, Zambia and Chile. In every one of the Copper mills we were able to identify the Electro-winning building, power plants and the CCDs.

Table 2 Location and CCD characteristics of sample Copper and Uranium mills

Sl. No.	Facility Name	CCD Diameter (m)	Number of CCD	Latitude - Longitude
Copper Mills				
1	Chino, U S A	116.00	2	32.79 N 108.06 W
2	Pinto Valley, U S A	107.00	3	33.39N 110.97W
3	Escondida, Chile	126.80	5	24.26 S 69.05 W
4	Carlotta, U S A	106.80	3	33 23 N 110 59 W
5	Cananea, Mexico	122.00	4	30.97 N 110.30 W
6	Grasberg, Indonesia	110.00	1	04 03 S 137 07 E
7	Twin Buttes, U S A	110.00	4	31 52 N 111 06 W
8	Phelps Dodge, U S A	90.00	6	33 04 N 109 20 W
9	Phelps Dodge, U S A	110.00	6	33 04 N 109 20 W
10	Nchanga, Zambia	76.00	4	12 32 S 27 50 E
Uranium Mills				
11	Feldiora, Romania	28.01	4	45 50 N 25 30E
12	Rabbit Lake, Canada	30.01	4	58 15 N 103 40 W
13	Rozna, Czech Republic	24.98	5	49 30 N 16 14 E
14	Sweet Water, U S A	9.75	6	42 03 N 107 54 W
15	Arlit, Niger	23.01	6	18 47 N 7 21 E
16	Krasnokamensk, Russia	52.01	6	50 06 N 118 11 E
17	Langer, Namibia	23.15	7	22 49 S 15 20 E
18	McClean Lake, Canada	12.85	8	58 21 N 103 50 W
19	Key Lake , Canada	20.00	8	57 13 N 105 40 W
20	Ranger, Australia	34.65	8	12 41 S 132 55 E
21	Rossing, Namibia	56.32	10	22 28 S 15 03 E
22	Olympic Dam, Australia	15.00	5	30 27 S 136 52 E
23	Turamdih, India	13.00	3	22 43 N 86 11 E
24	Dera Ghazi khan, Pakistan	15.00	6	29 59 N 70 35 E

Figure 6 is a plot of the CCD diameters of the various Copper and Uranium mills in our sample set.

From Figure 6 it appears that the diameter of the CCDs in Copper and Uranium mills can be used to separate them out. The threshold for separation is a little larger than 60 m. While the CCD diameter by itself shows promise as a discriminator, a closer scrutiny of the CCD process suggests that the diameter by itself may not be sufficient to capture the

volume of throughput which is the phenomenon we should try and capture. There is also the possibility that the particular sample of Copper and Uranium mills that we have chosen provides this clear separation. Other samples may show greater variability in CCD diameters leading to overlaps that could increase the probability of misclassification. It may therefore be necessary to add another feature that could improve our discriminating capabilities.

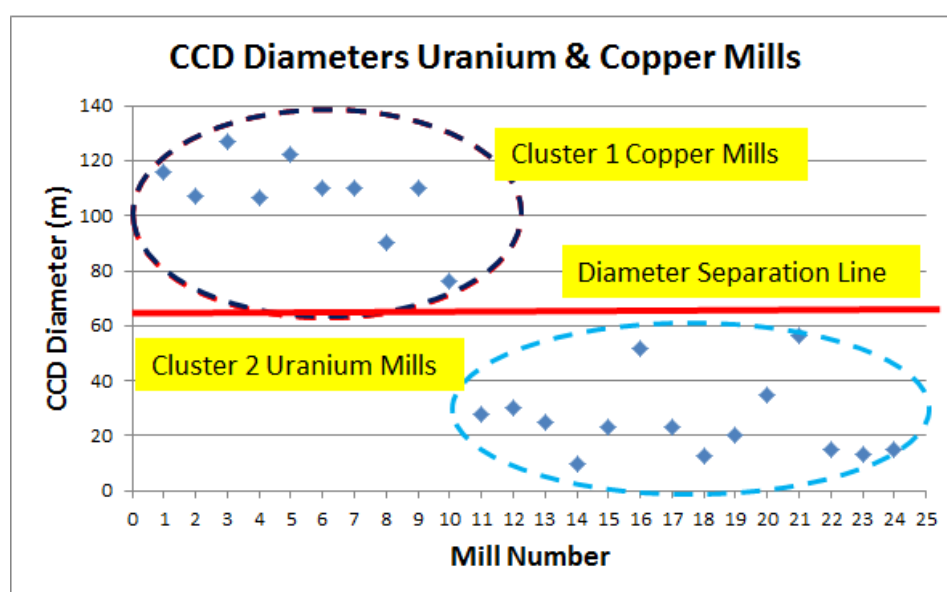


Figure 6 CCD Diameters of Uranium and Copper Mills

Since the phenomenon that we are trying to capture is volume based we could add the number of CCDs (also easily seen in a satellite image) as another feature to our classification procedure that would improve and add to the robustness of the separation between our two classes.

Figure 7 shows the scatter plots of the diameters and the number of CCDs. From the Figure it is clear that though there is some overlap with regard to the number of CCDs the two clusters are clearly separable. One cluster represents the Copper mills and the other represents the Uranium mills.

The sample means and standard deviations for the two clusters are shown in Table 3.

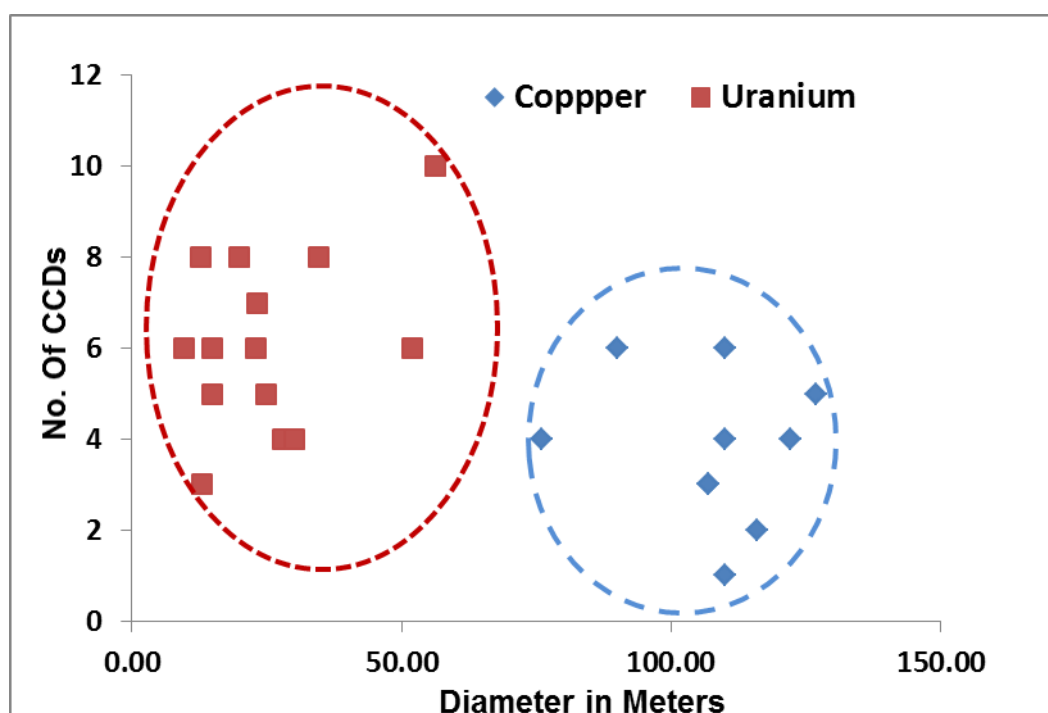


Figure 7 Scatter Plot of the CCD diameter and numbers from sample Uranium and Copper mills.

Table 3. Mean & Standard Deviation of the Uranium and Copper clusters

Feature	CCD Diameter (m)		No. of CCDs	
	Mean	Standard Deviation	Mean	Standard Deviation
Copper	107.46	14.81	3.8	1.62
Uranium	25.55	14.12	6.1	1.91

The variability in the diameters for the two clusters is about the same. The mean diameter of the Uranium CCDs is significantly smaller than the mean diameter of the Copper CCDs. It is also apparent from the scatter plot that the two clusters can be separated using the diameters alone. The

maximum diameter of the Uranium CCD is 56.32 which is less than the minimum diameter of 76.0 meters of the Copper CCD.

If we were to take this variable alone then we could classify using a simple criterion of closeness to the respective cluster means. Taking the midpoint of the distance between the two means we could decide to classify any sample point with diameter less than 66.50 m into the Uranium cluster. However as we had stated earlier adding another feature such as the number of CCDs will add to the robustness of our classification algorithm and also take care of sample bias.

Taken together the two variables - the number of CCDs and the diameter - represent the volume of ore handled by a mill and a classification criterion based on them will reduce the misclassification errors.

If such an approach is used then in order to decide whether a new sample point belongs to a Uranium mill or a Copper mill, we need to use discriminant functions. Discriminant functions could be defined in terms of the available statistics such as the mean and standard deviation.

There are two approaches in defining the discriminant functions. The simplest case takes into account only the Euclidean distance without considering the variability within the clusters. This is the minimum distance classifier. The Mahalanobis distance classifier takes into account the dispersion within and between the clusters, which is expressed in the form of the variance – covariance matrices of the two clusters.

7. Minimum Distance Classifier

We discuss below the minimum distance classifier and its discriminant functions.

Suppose we have to decide whether an unknown mill is a Uranium mill or a Copper mill based on the two characteristics – Diameter of the CCD and the number of CCDs, we could proceed as follows.

We define the vector representing these two characteristics as

$X = (x_1 \ x_2)$ where,

x_1 = Diameter of the CCD

x_2 = No. of CCDs

There are two clusters C1 representing Uranium and C2 representing Copper.

Our objective is to find decision functions $d_1(X)$ and $d_2(X)$ such that if a sample vector x belongs to C1, then $d_1(x)$ will be greater than $d_2(x)$.

The boundary function (which in this case of two features will be a straight line) separating the two clusters is defined as

$$d(X) = d_1(X) - d_2(X) = 0 \quad (1)$$

We will obtain this boundary line using the sample data in Table 2.

Following the method provided by Gonzalez and Woods [22], the distance function turns out to be for cluster C1 (Uranium)

$$d_1(X) = m_1 * x_1 + m_2 * x_2 - 0.5 (m_1^2 + m_2^2) \quad (2)$$

where m_1 and m_2 are the sample mean diameter of the CCD and sample mean number of CCDs. This is calculated from all the data belonging to the Uranium mills.

Similarly, by putting the values of the sample mean diameter of the CCD and the sample mean number of CCDs corresponding to the Copper mills, in the expression (2) above we will obtain the decision function $d_2(X)$.

Using the data from the sample we have,

$$\text{For Uranium } d_1(X) = 25.55 x_1 + 6.1 x_2 - 345.0063 \quad (3)$$

$$\text{For Copper } d_2(X) = 107.46 x_1 + 3.8 x_2 - 5781.046 \quad (4)$$

The decision line (Equation 1 above) separating the two clusters after simplification reduces to

$$35.61304 * x_1 - x_2 - 2363.496 = 0 \quad (5)$$

This boundary line is shown as AB in the Figure 8. This line, since it is based on Euclidean distance, will be perpendicular to the line joining the means of the two clusters. Any point falling to the right of the line will belong to a Copper mill and any point falling to the left of the line will be classified as a Uranium Mill.

It appears that this line of separation is almost entirely determined by the diameter of the CCD. So, the line is almost vertical and also passes through the value 66.37 meters on the X – axis.

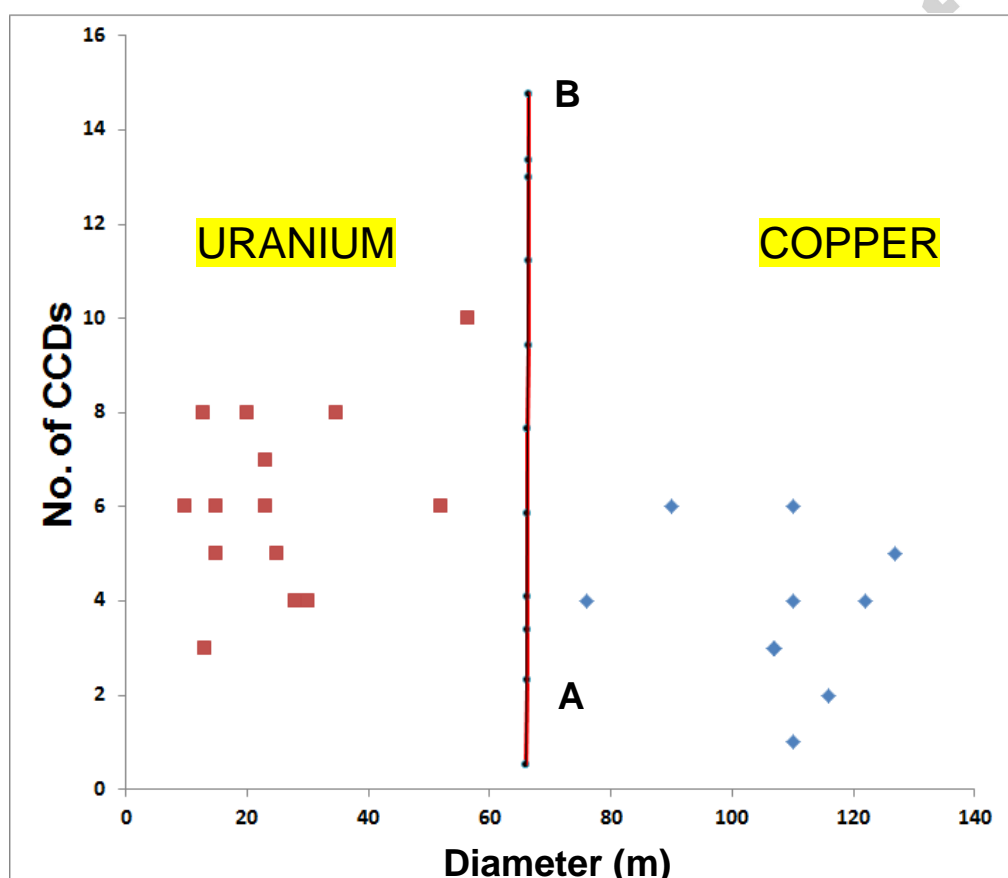


Figure 8 Decision Line AB separating the Uranium and Copper Clusters

There are problems with the simple Euclidean distance measure since it does not take into account the variability in the measured values. In order to take care of this problem it may be worthwhile to consider a

Mahalanobis distance measure that takes into account the covariance between the two features in our study. It is also superior to the Euclidean distance because it considers the variance of points in the two clusters. Essentially the Mahalanobis distance measure takes the mean and variance – covariance of the two variables. An important assumption is that the variance-covariance matrices for the two clusters are the same. This enables us to get a pooled variance-covariance matrix from our sample data.

The general approach is the same here as in the case of the minimum distance Classification.

In general, the Mahalanobis distance function for a cluster is defined as

$$[(x-M)^t S^{-1} (x-M)],$$

Where x is the sample vector defined earlier,

S^{-1} is the Inverse of the pooled variance – covariance matrix for the two clusters,

M is the mean vector.

By putting the respective mean values of the two clusters in this expression, we will have, the two distance functions $d_1(X)$ and $d_2(X)$ for the two clusters, which can be computed from the sample data in hand.

The Classifier function, which is again a straight line is defined as before

$$d(X) = d_1(X) - d_2(X) = 0 \dots\dots\dots (6)$$

Without going into the mathematics, the final form of the equation of the separating line obtained from the sample data is:

$$x_2 = 0.32071 * x_1 - 16.3788$$

or

$$d(x) = x_2 - 0.32071 * x_1 + 16.3788 = 0$$

This is shown in Figure 9 as line CD for the same scatter plot. Clearly this line is influenced by both the characteristics. This line is not perpendicular to the line joining the means of the two clusters. The mid point of the line joining the means of the two clusters will however lie on this line.

Any unknown sample vector x will be classified as belonging to cluster C1 or Uranium mill if $d(x) > 0$ and into Cluster C2 otherwise.

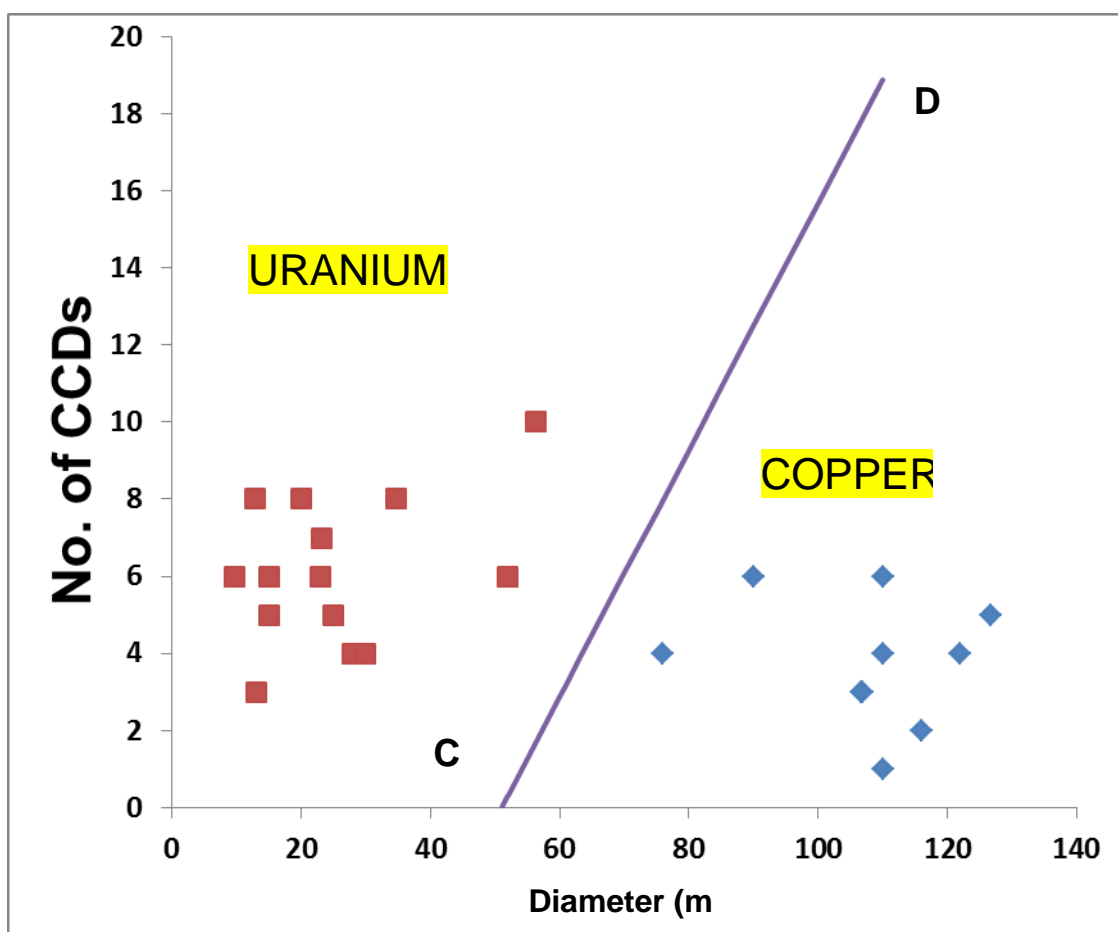


Figure 9 Decision Line CD separating the Uranium and Copper Clusters

8. Decision Algorithm to Differentiate a Uranium Mill from a Copper Mill

Our earlier study [18] demonstrated that CCDs, solvent extraction and ion exchange equipment have spatial signatures recognizable in satellite images whenever they are present. The need to discriminate a Uranium

mill from a Copper tailings extraction plant led us to look for features that are present in a Copper mill but not in a Uranium mill. This exploration led us to a decision tree that takes into account only the spatial signatures of the equipment used [16]. For clarity this decision tree is shown in Figure 10.

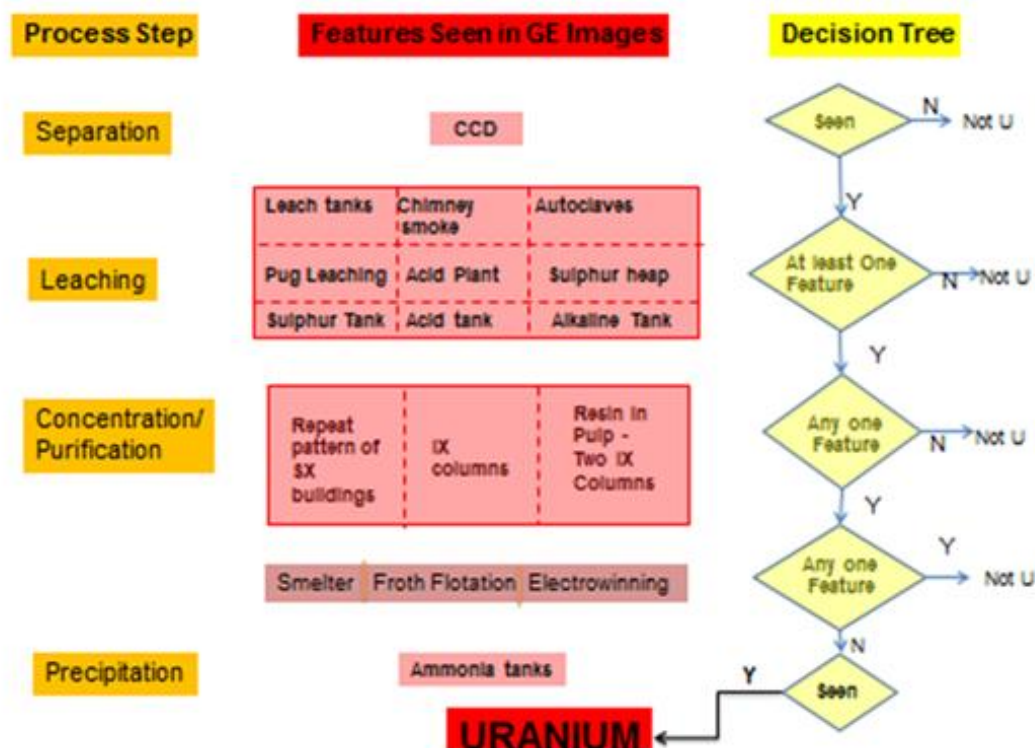


Figure 10 Decision Tree to Differentiate a Uranium Mill from a Copper Mill

In this paper we note that high resolution commercial satellite images also provide us a way to make measurements and determine the size of the facility. While the Electro-winning facility is present in a Copper mill and absent in a Uranium mill and can be used to separate the two, the common feature such as CCDs or power plants can also be used to distinguish the two mills based on their sizes.

The power plants are not always present in a Uranium mill. They are however always present in a Copper extraction plant associated with the

electro- winning facility. When present in a Uranium mill, the power plants are not very large.

We observed that in the case of Nchanga plant the power plant occupies an area of 75 m X 120 m, while the power plant at Ranger occupies an area of 22m X 35 m. In many of the Uranium mills that we analysed, we could not locate a power plant in the mill complex.

In addition we can see from the analysis carried out in this paper that the size and the number of CCDs in a milling facility can also be used to decide whether a mill is a Uranium mill or not.

In our image analysis we noted that the CCDs are the most distinguishing feature in a Uranium mill. They are immediately visible and their circular feature cannot be missed. The equipment associated with leaching can be identified more often because of their presence close to the CCDs. It is difficult to give a spatial description to these equipment, however. Similarly, although the solvent extraction buildings exhibit a repetitive pattern, it requires considerable training to the eye to recognize it in a satellite image.

Since Copper mills are most often confused with Uranium mills, in a situation where we are unable to decide whether the mill is a Copper mill or a Uranium mill, the dimensions of the CCD can be used as a very good discriminator.

Thus we arrive at the following decision tree (Figure 11) to differentiate a Uranium mill from a Copper mill in a Google Earth image. The dimensions of the CCD provide additional evidence to decide whether a suspected mill is Uranium or not. This decision algorithm will classify a mill as not Uranium, if an electro-winning facility is seen along with the CCDs and other features. Essentially this means that any mill that has an electro-winning facility will not be a Uranium mill.

What this decision algorithm tries to do is this:

If there are CCDs, and no electro-winning facility is seen, and if the leaching and solvent extraction facilities are not clearly identifiable, then by computing the discriminant function based on the CCD characteristics we could unequivocally decide whether the mill is a Uranium mill or not.

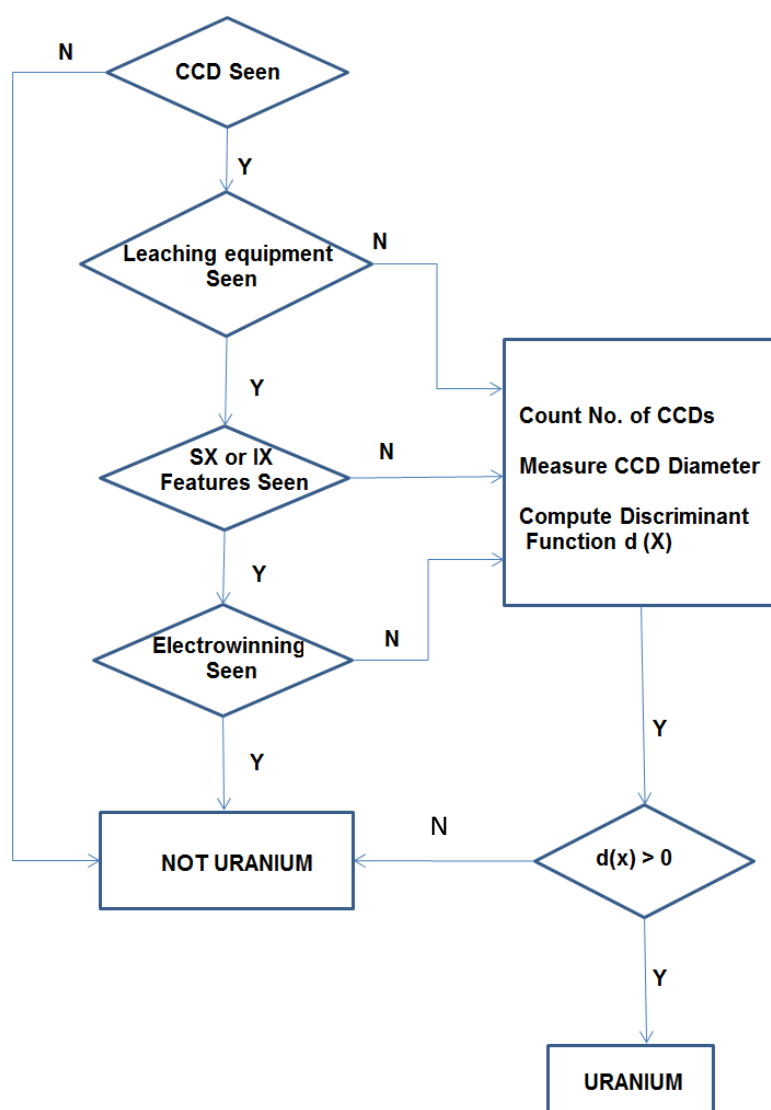


Figure 11 A Decision Algorithm to identify a Uranium mill and Differentiate it from a Copper mill.

9. Conclusion

Starting with the premise that Identifying Uranium milling operations is not possible using only hyper-spectral satellite images, the paper suggests that an understanding of the extraction process and the flow diagrams and the equipment used for this purpose is the first step in trying to identify a Uranium extraction facility from high resolution commercial satellite images.

The spatial features of the equipment used and their connections help to define what an interpreter should be looking for in a satellite image. By looking at a number of Uranium extraction process facilities called a Uranium mill all over the world, it is possible to characterize a Uranium mill in terms of specific objects or spatial features. The way these objects are connected or the way the process flow is exhibited in these sites also provides an important clue to decide whether the facility is a Uranium mill or not.

Since Copper mills may be confused for a Uranium mill, additional signatures are required. The features seen only in a Copper mill such as the electro-winning building and the associated power plant are used to resolve this confusion. The differential sizes of common equipment seen in a Uranium mill and Copper mill are also found to be useful here. The dimensions and numbers of CCDs seen in both Copper and Uranium mills are used to discriminate a Uranium mill from a Copper mill.

A decision algorithm is thus arrived at which incorporates all of these elements.

The methodology provided can be suitably modified and automated to define the rules for object based image analysis to identify a Uranium mill and discriminate it from a Copper mill.

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